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Control of industrial robot using neural network compensator

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Abstract

In the paper is considered synthesis of the controller with tachometric feedback with feedforward compensation of disturbance torque, velocity and acceleration errors. It is difficult to obtain the desired control performance when the control algorithm is only based on the robot dynamic model. We use the neural network to generate auxiliary joint control torque to compensate these uncertainties. The two-layer neural network is used as the compensator. The main task of control system here is to track the required trajectory. Simulations are done in MATLAB for $R_zR_yR_y$ robot minimal configuration.

1 Introduction

Tracking control of an industrial robot has been a difficult challenging problem to be solved for decades. A lot of research has dealt with the tracking control problem. As the most popular approach, computed-torque method or inverse dynamic control method is used most for robot dynamic control. It is difficult to obtain the desired control performance when the control algorithm is only based on the robot dynamic model.

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Robots have to face many uncertainties in their dynamics, in particular structured uncertainty, such as payload parameter, and unstructured one, such as friction and disturbance.

Fuzzy logic, neural network and neuro-fuzzy systems have been applied for identification of nonlinear dynamics and robot control. Neural networks make use of nonlinearities, learning ability, parallel processing ability, and function approximation for applications in advanced adaptive control.

An approach and a systematic design methodology to adaptive motion control based on neural network is presented in [1]. The neuro controller includes a linear combination of a set of off-line trained neural networks and an updated law of the linear combination coefficients to adjust robot dynamics and payload uncertain parameters. Simulation results, showing the practical feasibility and performance of the proposed approach to robotics, are given.

In [2] a new neural network controller for the constrained robot manipulators in task space is presented. The neural network is used for adaptive compensation of the structured and unstructured uncertainties. It is shown that the neural network adaptive compensation is universally able to cope with totally different classes of system uncertainties. Detailed simulation results are given to show the effectiveness of the proposed controller.

In [3] a kind of recurrent fuzzy neural network is constructed by using recurrent neural network to realize fuzzy inference. Simulation experiments are made by applying proposed fuzzy neural network on robotic tracking control problem to confirm its effectiveness.

A neural-network-based adaptive tracking control scheme is proposed for a class of nonlinear systems in [4]. Using this scheme, not only strong robustness with respect to uncertain dynamics and nonlinearities can be obtained, but also the output tracking error between the plant output and the desired reference output can asymptotically converge to zero.

This paper is organized as follows. In section II, several properties of robot dynamics are introduced. In section III, the control scheme is proposed, where neural network is utilized to compensate the uncertainties of the industrial robot. The proposed control algorithm is verified through computer simulations for. In section IV are presented results of simulation for the three-segment robot of the $R_zR_yR_y$ minimal configuration. Section V gives concluding remarks.

2 Properties of robot dynamic model and uncertainties

An industrial robot is defined as an open kinematic chain of rigid links. The numeration of segments starts from the support (denoted by zero, i.e.$i = 0$) towards the open end of the chain ($i = n$). Each degree of freedom of the manipulator is powered by independent torques. Using the Langrangian formulation, the equations of motion of an n-degree-of-freedom robot can be written as:

$$H(\theta)\ddot{\theta} + C\left(\theta, \dot{\theta}\right) + G(\theta) + F\left(\theta, \dot{\theta}, \ddot{\theta}\right) = M, \tag{1}$$

where: θ are the generalized coordinates; $H(\theta)$ is the symmetric, positive-definite inertia matrix; $C\left(\theta, \dot{\theta}\right)$ is the vector of centrifugal and Coriolis torques; $G(\theta)$, $F\left(\theta, \dot{\theta}, \ddot{\theta}\right)$, M represent gravitational torques, uncertainty and applied joint torques, respectively.

The robot dynamic equations represent a highly nonlinear coupled, and multi-input multi-output system.

The friction in the dynamic equation (1) (part of uncertainty function) is of the form:

$$F_r\left(\dot{\theta}\right) = F_v\dot{\theta} + F_d\left(\dot{\theta}\right), \tag{2}$$

with F_v as the coefficient matrix of viscous friction and F_d as a dynamic friction term, since friction is dependent on angular velocity $\dot{\theta}$ only.

3 Control of robot using neural network compensator

The aim of controller synthesis consists of selection of structure and parameters such that the system obtains characteristics that were set in advance, with respect to transient process and stationary state. The actuators used in the industrial robots are hydraulic, pneumatic, or electrical. When actuators is electrical, then control system of industrial robot determines the voltage at the ends of rotor's coils of the actuator, such that the driving moments or forces ensure as good as possible tracking of the required trajectory of the manipulator segments' motion in real time.

In [5] is used position controller with tachometric feedback with feedforward compensation of disturbance torque, velocity and acceleration errors for the manipulator control. The control law of the i-th segment is:

$$u_{Ci}(t) = \frac{J_{efi}R_i}{k_{ii}n_i}\ddot{\theta}_{di} + \frac{B_{efi}R_i}{k_{ii}n_i}\dot{\theta}_{di} + \frac{k_{bi}}{n_i}\dot{\theta}_{di} + \frac{R_i n_i}{k_{ii}}\sum_{\substack{j=1\\ j\neq i}}^{n} H_{ij}\ddot{\theta}_j +$$

$$\frac{R_i n_i}{k_{ii}}C_i\left(\theta,\dot{\theta}\right) + \frac{R_i n_i}{k_{ii}}G_i\left(\theta\right) + k_{\theta i}\left(\theta_{di}-\theta_i\right) + \frac{k_{1i}k_{ti}}{n_i}\dot{\theta}_{di} - \frac{k_{1i}k_{ti}}{n_i}\dot{\theta}_i \quad (3)$$

where:

$$R_i k_{ii} n_i = \frac{1}{N_i}\dot{\theta}_{di} H_{ij} = H_{ij}\left(\theta_{k+1},...\theta_n\right), \quad k=\min\left(i,j\right)$$

$k_{ti}-$ is the tachometer constant,
$k_{\theta i}-$ is the conversion constant,
$k_{1i}-$ is the amplifier gain,
$\theta_{di}-$ is the desired angular displacement,
θ_i- is the actual angular displacement,
$k_{bi}-$ is the coefficient of the back electro-motor force,
$B_{efi}-$ is the effective damping coefficient,
$J_{efi}-$ is the effective moment of inertia,
R_i- is the rotor winding resistance,
$k_{ii}-$ is the torque constant,
$n_i = \frac{1}{N_i}-$ is the gear ratio,
$\dot{\theta}_{di}-$ is the desired angular velocity,
$H_{ij} = H_{ij}\left(\theta_{k+1},...\theta_n\right), \quad k=\min\left(i,j\right)$ $-$ are the terms of the inertial coefficients matrix,

$C_i\left(\theta,\dot{\theta}\right)=\sum\limits_{j=1}^{n}\sum\limits_{k=1}^{n}C_{ijk}\dot{\theta}_j\dot{\theta}_k$ - is the term of the vector of centrifugal and Coriolis torques,

$C_{ijk}=\frac{1}{2}\left(\frac{\partial H_{ij}}{\partial\theta_k}+\frac{\partial H_{ki}}{\partial\theta_j}-\frac{\partial H_{jk}}{\partial\theta_i}\right)-$ are the Christoffel's symbols of the first kind,

G_i- represents the action of gravitational forces.

In the appendix is presented determination of $k_{\theta i}$ and k_{1i}.

The H_{ij}, C_{ijk} and G_i in (3) are functions of physical parameters of industrial robots like links' masses, links' lengths, moments of inertia, payload parameter. The precise values of these parameters are difficult to acquire due to measuring errors, environment and payload variations. The position controller with tachometric feedback with feed-forward compensation of disturbance torque, velocity and acceleration errors, relies on strong assumptions that exact knowledge of robotic dynamics is precisely known and unmodeled dynamics has to be ignored, which is impossible in practical engineering.

We use the position controller with tachometric feedback with feed-forward compensation of disturbance torque, velocity and acceleration errors (controller, Fig.1). Also, we use the neural network to generate auxiliary joint control torque to compensate uncertainties. During the operation the coefficient of viscous and dry friction in joints and some actuator characteristics are rather slowly varying. There is a group of parameters of the robotic system which vary significantly and relatively fast, and which have big influence on the robot performance. Such parameters are masses, dimensions and moments of inertia of the payload, which is carried by the robot. The presence of the payload causes the change H_{ij}, C_{ijk} and G_i and uncertain parts denoted by $F_i\left(\theta,\dot{\theta},\ddot{\theta}\right)$. In this paper is considered the case when the uncertainty is the consequence of the working object parameters variation, i.e., its mass. It is assumed that both the minimum and maximum mass of the working object are known. The proposed control scheme is shown in Fig. 1.

Overall control law of the i-th segment reads:

$$u_i(t)=u_{C_i}(t)+u_{N_i}(t), \tag{4}$$

where $u_{C_i}(t)$ is defined like in (3), and

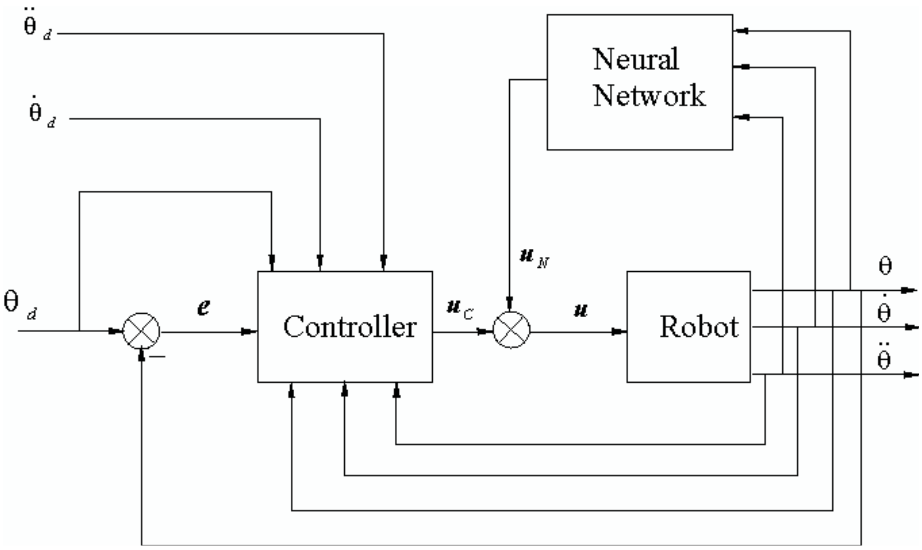

Figure 1: Proposed feedback neural compensator structure

$$u_{Ni}\left(t\right)=\frac{R_i n_i}{k_{ii}}F_i\left(\theta,\dot{\theta},\ddot{\theta}\right), \tag{5}$$

where $F_i\left(\theta,\dot{\theta},\ddot{\theta}\right)$ is uncertainty of the i-th segment.

In this work neural network is used to define $u_{Ni}\left(t\right)$. The two-layer neural network with m inputs and one output is shown in Fig.2. It is composed of an input buffer, a nonlinear hidden layer, and a linear output layer. For adapting parameters is used the backpropagation algorithm. The learning method requires set of data for training $P=\{p_1,p_2,...p_r\}$. Each element of the set, $p_k=(x_k,y_{zk})$ is defined by the input vector $x_k=(x_{1k}\,x_{2k}...x_{mk})$ and the desired response y_{zk}.

The inputs $x=(x_1\,x_2...x_m)$ are multiplied by weights $\omega_{ij}^{(1)}$ and summed at each hidden node. Then the summed signal at a node activates a nonlinear function (sigmoid function). Thus, the output y at a linear output node can be calculated from its inputs as follows:

$$y=\sum_{j=1}^{n_H}\omega_{j1}^{(2)}\frac{1}{1+e^{-\left(\sum\limits_{i=1}^{m}x_i\omega_{ij}^{(1)}+b_j^{(1)}\right)}}+b_1^{(2)}, \tag{6}$$

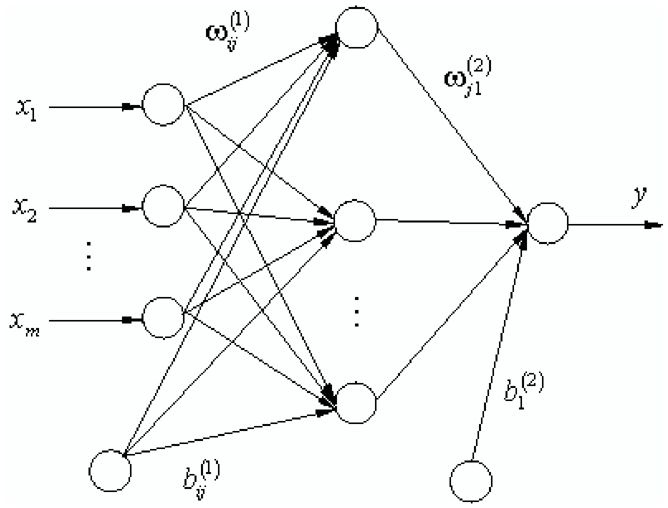

Figure 2: Multilayer feedforward neural network structure

where m is the number of inputs, n_H is the number of hidden neurons, x_i is the i-th element of input, $\omega_{ij}^{(1)}$ is the first layer weight between the i-th input and the j-th hidden neuron, $\omega_{j1}^{(2)}$ is the second layer weight between the j-th hidden neuron and output neuron, $b_j^{(1)}$ is a biased weight for the j-th hidden neuron and $b_1^{(2)}$ is a biased weight for the output neuron.

The weight updating law minimizes the function:

$$\varepsilon = \frac{1}{2}\left(y - y_z\right)^2 . \tag{7}$$

The backpropagation update rule for the weights with a momentum term is:

$$\Delta\omega\left(t\right) = -\eta\frac{\partial\varepsilon}{\partial\omega} + \alpha\Delta\omega\left(t-1\right), \tag{8}$$

where η is the update rate and α is the momentum coefficient. Specifically,

$$\frac{\partial\varepsilon}{\partial\omega_{ij}^{(1)}} = \left(y - y_z\right)\omega_{j1}^{(2)} x_i \frac{e^{-\left(\sum\limits_{i=1}^{m} x_i\omega_{ij}^{(1)} + b_j^{(1)}\right)}}{\left[1 + e^{-\left(\sum\limits_{i=1}^{m} x_i\omega_{ij}^{(1)} + b_j^{(1)}\right)}\right]^2} \tag{9}$$

$$\frac{\partial \varepsilon}{\partial b_j^{(1)}} = (y - y_z)\,\omega_{j1}^{(2)} \frac{e^{-\left(\sum\limits_{i=1}^{m} x_i \omega_{ij}^{(1)} + b_j^{(1)}\right)}}{\left[1 + e^{-\left(\sum\limits_{i=1}^{m} x_i \omega_{ij}^{(1)} + b_j^{(1)}\right)}\right]^2} \tag{10}$$

$$\frac{\partial \varepsilon}{\partial \omega_{j1}^{(2)}} = (y - y_z) \frac{1}{\left[1 + e^{-\left(\sum\limits_{i=1}^{m} x_i \omega_{ij}^{(1)} + b_j^{(1)}\right)}\right]^2} \tag{11}$$

$$\frac{\partial \varepsilon}{\partial b_1^{(2)}} = y - y_z. \tag{12}$$

4 Simulation results

Simulations were done for the robot shown in Fig.3 ($R_z R_y R_y$ minimal configuration).

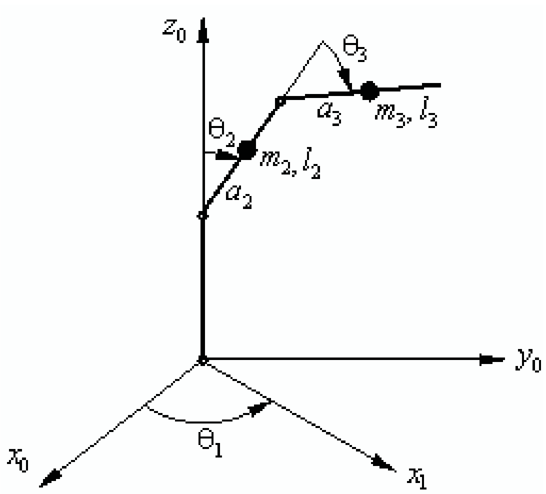

Figure 3: The three segment industrial robot of the $R_z R_y R_y$ configuration

Characteristic values of the shown robot are:
lengths of segments - $l_1 = 0.75,\ m$; $l_2 = 0.5,\ m$; $l_3 = 0.5,\ m$

positions of centres of masses -

$$a_1 = 0.4,\, m;\quad a_2 = 0.2,\, m;\quad a_3 = 0.2,\, m;$$

masses of segments -

$$m_1 = 2.27,\ kg;\quad m_2 = 15.91,\ kg;\quad m_3 = 6.82,\ kg;$$

moments of inertia -

$$J_{\xi 1} = 0.0194,\, kgm^2;\quad J_{\eta 1} = 0.0388,\, kgm^2;\quad J_{\zeta 1} = 0.0267,\, kgm^2;$$

$$J_{\xi 2} = 0.01,\, kgm^2;\quad J_{\eta 2} = 3.7691,\, kgm^2;\quad J_{\zeta 2} = 3.6959,\, kgm^2;$$

$$J_{\xi 3} = 0.0904,\, kgm^2;\quad J_{\eta 3} = 0.2245,\, kgm^2;\quad J_{\zeta 3} = 0.2842,\, kgm^2;$$

coefficient of the viscous friction in segments bearings -
$B_i = 0.2,\, \frac{Nms}{rad}$;
gear ratio -
$n_1 = n_2 = n_3 = 0.01.$
The structural resonant frequency: $\omega_{r1} = 30,\, \frac{rad}{s}$; $\omega_{r2} = 30,\, \frac{rad}{s}$; $\omega_{r3} = 35,\, \frac{rad}{s}$.

Mass load: $m_{t\,\min} = 0,\, kg$; $m_{t\,\max} = 2.5,\, kg$.

For the robot shown in Fig. 3:

$$\sum_{\substack{j=1 \\ j \neq 1}}^{3} H_{1j}\ddot{\theta}_j = 0,$$

$$C_1\left(\theta, \dot{\theta}\right) = [(m_2 a_2^2 + m_3 l_2^2 + J_{\xi 2} - J_{\zeta 2}) \sin 2\theta_2 +$$

$$(m_3 a_3^2 + J_{\xi 3} - J_{\zeta 3}) \sin 2\left(\theta_2 + \theta_3\right) + 2 l_2 m_3 a_3 \sin\left(2\theta_2 + \theta_3\right)]\, \dot{\theta}_1 \dot{\theta}_2 +$$

$$[(m_3 a_3^2 + J_{\xi 3} - J_{\zeta 3}) \sin 2\left(\theta_2 + \theta_3\right) +$$

$$2 l_2 m_3 a_3 \sin\theta_2 \cos\left(\theta_2 + \theta_3\right)]\, \dot{\theta}_1 \dot{\theta}_3,$$

$$G_1\left(\theta\right) = 0,$$

$$\sum_{\substack{j=1\\ j\neq 2}}^{3} H_{2j}\ddot{\theta}_j = \left[J_{\eta 3} + m_3 a_3^2 + m_t l_3^2 + (m_3 a_3 + m_t l_3)\, l_2 \cos\theta_3\right] \ddot{\theta}_3.$$

$$C_2\left(\theta,\dot{\theta}\right) = -\tfrac{1}{2}\left[(m_2 a_2^2 + m_3 l_2^2 + J_{\xi 2} - J_{\zeta 2})\sin 2\theta_2 + \right.$$

$$\left.(m_3 a_3^2 + J_{\xi 3} - J_{\zeta 3})\sin 2(\theta_2+\theta_3) + \ 2 l_2 m_3 a_3 \sin(2\theta_2 + \theta_3)\right]\dot{\theta}_1^2 -$$

$$2 l_2 m_3 a_3 \sin\theta_3 \dot{\theta}_2 \dot{\theta}_3 - m_3 a_3 l_2 \sin\theta_3 \dot{\theta}_3^2,$$

$$G_2(\theta) = -(m_2 a_2 + m_3 l_2)\, g \sin\theta_2 - \ m_3 a_3 g \sin(\theta_2+\theta_3)$$

$$\sum_{\substack{j=1\\ j\neq 3}}^{3} H_{3j}\ddot{\theta}_j = \left[J_{\eta 3} + m_3 a_3^2 + m_3 a_3 l_2 \cos\theta_3\right] \ddot{\theta}_2.$$

$$\begin{aligned} C_3\left(\theta,\dot{\theta}\right) \ &= \ -\frac{1}{2}\ \left[\left(m_3 a_3^2 + J_{\xi 3} - J_{\zeta 3}\right)\sin 2(\theta_2+\theta_3) + \right. \\ &\left. 2 l_2 m_3 a_3 \sin\theta_2 \cos(\theta_2+\theta_3)\right]\dot{\theta}_1^2 + m_3 a_3 l_2 \sin\theta_3 \dot{\theta}_2^2, \\ & G_3(\theta) = -m_3 a_3 g \sin(\theta_2+\theta_3)\,. \end{aligned}$$

Functions in equation (5) for the considered robot are:

$$\begin{aligned} & F_1\left(\theta,\dot{\theta},\ddot{\theta}\right) = [m_t l_2^2 \sin 2\theta_2 + m_t l_3^2 \sin 2(\theta_2+\theta_3) + \\ & 2 l_2 m_t l_3 \sin(2\theta_2+\theta_3)]\,\dot{\theta}_1\dot{\theta}_2 + [m_t l_3^2 \sin 2(\theta_2+\theta_3) + \\ & 2 l_2 m_t l_3 \sin\theta_2 \cos(\theta_2+\theta_3)]\,\dot{\theta}_1\dot{\theta}_3, \\ & F_2\left(\theta,\dot{\theta},\ddot{\theta}\right) = (m_t l_3^2 + m_t l_3 l_2 \cos\theta_3)\,\ddot{\theta}_3 - \tfrac{1}{2}\,[m_t l_2^2 \sin 2\theta_2 + \\ & m_t l_3^2 \sin 2(\theta_2+\theta_3) + 2 l_2 m_t l_3 \sin(2\theta_2+\theta_3)]\,\dot{\theta}_1^2 \\ & - 2 l_2 m_t l_3 \sin\theta_3 \dot{\theta}_2\dot{\theta}_3 - m_t l_3 l_2 \sin\theta_3 \dot{\theta}_3^2 - \ m_t l_2 g \sin\theta_2 - \\ & m_t l_3 g \sin(\theta_2+\theta_3)\,, \end{aligned} \qquad (13)$$

$$F_3\left(\theta,\dot{\theta},\ddot{\theta}\right)=\left(m_t l_3^2+m_t l_3 l_2\cos\theta_3\right)\ddot{\theta}_2-$$

$$\tfrac{1}{2}\left[m_t l_3^2\sin 2\left(\theta_2+\theta_3\right)+2l_2 m_t l_3\sin\theta_2\cos\left(\theta_2+\theta_3\right)\right]\dot{\theta}_1^2+$$

$$m_t l_3 l_2\sin\theta_3\dot{\theta}_2^2-m_t l_3 g\sin\left(\theta_2+\theta_3\right).$$

For the driving of the first and the third segment the DC motor U9M4T was chosen, and for the second segment, which is the most exposed to influence of moment due to gravitational forces, the DC motor U12M4T was chosen. The characteristic values for the used motors are given in Table 1.

Model	U9M4T	U12M4T
Moment of inertia of the rotor $J_a,\ kgm^2$	$56.484\cdot10^{-6}$	$233\cdot10^{-6}$
Coefficient of the viscous friction $B_m,\ Nms/rad$	$80.913\cdot10^{-6}$	$303.39\cdot10^{-6}$
Coefficient of torque $k_i,\ Nm/A$	0.043	0.10167
Back electro-motor force constant $k_b,\ Vs/rad$	0.04297	0.10123
Resistance of the rotor coil $R,\ \Omega$	1.025	0.91
Maximum driving torque $M_{m\max},\ Nm$	1.4	2.8
Tachometer constant $k_t,\ Vs/rad$	0.02149	0.05062

Table 1: The characteristic values of the used motors

The controller gains are selected as:
$k_{\theta1}=384.55,\ k_{\theta2}=257.81,\ k_{\theta3}=123.16,\ k_{11}=21.75,$
$k_{12}=4.73,\ k_{13}=4.44.$ (See Appendix)

The input and output variables of the neural networks are shown in Fig. 4.

One of the most interesting properties of neural networks is that they are universal approximators ([6]). A multlayer neural network can approximate the function defined in (5) with its bounded inputs: $\theta_1=\theta_2=\theta_3=\left[-\frac{\pi}{2},\ \frac{\pi}{2}\right]$, $\dot{\theta}_1=\dot{\theta}_2=\dot{\theta}_3=\left[-1.5\frac{rad}{s},\ 1.5\frac{rad}{s}\right]$, $\ddot{\theta}_1=\ddot{\theta}_2=\ddot{\theta}_3=\left[-5\frac{rad}{s^2},\ 5\frac{rad}{s^2}\right]$. Values for n_H, η and α are 6, 0.01 and 0.9, respectively.

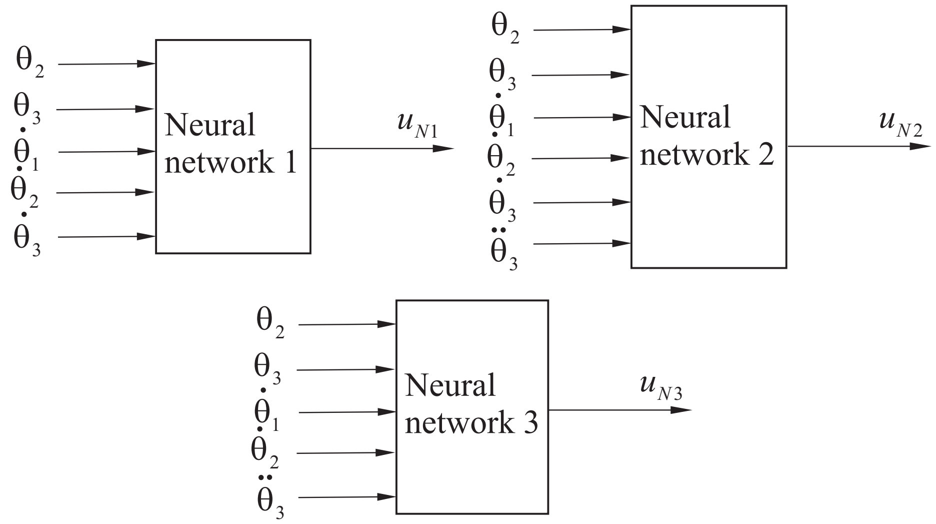

Figure 4: Illustration of the input and the output variables of neural network compensator

The training set predicated that $m_{t\min} = 0$ and $m_{t\max} = 2.5,\ kg$. The data set for neural network training is formed based on equation (5) and functionsF_i, which are given in (13).

The simplest and most common way of specifying a joint trajectory $\theta_i(t)$ is to specify the initial and final values of $\theta_i(t)$ and $\dot{\theta}_i(t)$. These are normally stated as: $\theta_i(0) = \theta_{iA}$, $\theta_i(t_{\max}) = \theta_{iB}$, $\dot{\theta}_i(0) = 0$, $\dot{\theta}_i(t_{\max}) = 0$, where $t_{\max}$ is the final time and the robotic hand is required to be at rest initially at time $t = 0$ and to come to rest at time $t = t_{\max}$. These constraints can be satisfied by third-degree polynomials in time ([7], [8]).

The gripper was moving from the point A (-0.718, 0.304, 1,639) to point B (0.242, 0.075, 1.646). It is assumed that there are no obstacles in the working space. The desired joint angle trajectories (internal coordinates) for a robot to track are:

$$\theta_i(t) = \theta_{iA} + \frac{3}{t_{\max}^2}(\theta_{iB} - \theta_{iA})\,t^2 - \frac{2}{t_{\max}^3}(\theta_{iB} - \theta_{iA})\,t^3, \quad i = 1, 2, 3,$$

where: $\theta_{1A} = -0.4\ rad$; $\theta_{2A} = -1\ rad$; $\theta_{3A} = 0.2\ rad$; $\theta_{1B} = 0.3\ rad$; $\theta_{2B} = -0.1\ rad$; $\theta_{3B} = 0.75\ rad$.

The time taken for performing the motion is $t_{\max} = 2\ s$.

In Fig.5 is given the variation of the internal coordinates during the task execution. In Fig.6 is given the variation of the tracking errors of the trajectory for the case of application of the proposed controller structure.

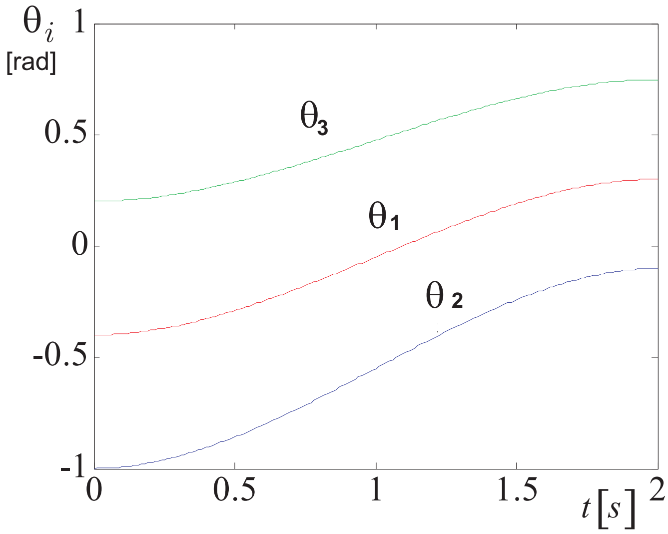

Figure 5: Variation of the internal coordinate $\theta_i\,(t)$ along the trajectory

5 Conclusion

Results of simulation, presented in this paper, show that the application of the neural network compensator to control of industrial robots gives satisfactory results.

Robots are complicated nonlinear dynamical systems with unmodeled dynamics and unstructured uncertainties. These dynamical uncertainties make the controller design for manipulators a difficult task in the framework of classical control. One of the most important industrial robot operations is the control of the robot to track a given trajectory. Most commercial robot systems are currently equipped with conventional PID controllers due to their simplicity in structure and

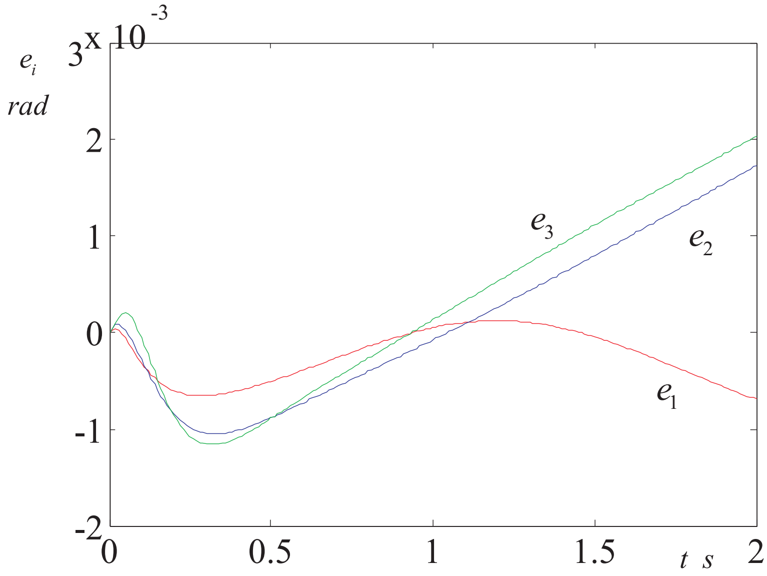

Figure 6: Variation of the tracking errors

ease of design. Using PID control, however, it is difficult to achieve a desired tracking control performance since the dynamic equations of a mechanical manipulator are tightly coupled, highly nonlinear and uncertain. In order to improve the tracking control performance under uncertainty, this paper presents a new hybrid control scheme for the industrial robot, which consists of a neural network compensator and a conventional controller with tachometric feedback with feedforward compensation of disturbance torque, velocity and acceleration errors.

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Appendix

Determination of $k_{\theta i}$ and k_{1i}

The characteristic equation for the closed-loop controller ([5]) is:

$$s^2 + \left[\frac{B_{efi}}{J_{efi}} + \frac{k_{ii}\left(k_{bi} + k_{1i}k_{ti}\right)}{R_i J_{efi}}\right] s + \frac{n_i k_{\theta i} k_{ii}}{R_i J_{efi}} = 0, \tag{14}$$

which is conventionally expressed as:

$$s^2 + 2\xi_i \omega_{ni} s + \omega_{ni}^2 = 0, \tag{15}$$

where ξ_i is the damping ratio and ω_{ni} the undamped natural frequency.

From (14) and (15), one obtains:

$$\omega_{ni} = \sqrt{\frac{n_i k_{\theta i} k_{ii}}{R_i J_{efi}}} \tag{16}$$

and

$$\xi_i = \frac{R_i B_{efi} + k_{ii}\left(k_{bi} + k_{1i}k_{ti}\right)}{\sqrt{k_{\theta i} k_{ii} n_i R_i J_{efi}}}. \tag{17}$$

In [5] is suggested that for a conservative design, with a safety factor of 200 percent, one sets the undamped natural frequency ω_{ni} to no more than one-half of the structural resonant frequency ω_{ri}.

$$\omega_{ni} \leq \frac{1}{2}\omega_{ri}. \tag{18}$$

Thus by (16) and (18), one obtains:

$$k_{\theta i} \leq \frac{\left(\frac{\omega_{ri}}{2}\right)^2 R_i J_{efi}}{k_{ii} n_i}. \tag{19}$$

As the existence of the overshoot during the motion of the manipulator segments is undesirable, since it can lead to contact of the manipulator with some objects in its environment, tendency is always for the response to be either critically damped or over critically damped. Then:

$$\xi_i = \frac{R_i B_{efi} + k_{ii}\left(k_{bi} + k_{1i} k_{ti}\right)}{\sqrt{k_{\theta i} k_{ii} n_i R_i J_{efi}}} \geq 1. \tag{20}$$

From (20) follows:

$$k_{1i} \geq \frac{2\sqrt{k_{\theta i} k_{ii} n_i R_i J_{efi}} - R_i B_{efi}}{k_{ii} k_{ti}} - \frac{k_{bi}}{k_{ti}} \tag{21}$$

Since the minimal value of the relative damping coefficient appears when $J_{efi} = J_{efi\,\max}$, the values of gains are calculated in such a way that the response is critically damped with respect to $J_{efi\,\max}$. In this way, for the smaller values of the effective moment of inertia, it is ensured that the value of the relative damping factor is greater than unity, namely, the desired aperiodic response is ensured.

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Upravljanje industrijskim robotom korišćenjem neuronske mreže kao kompenzatora

UDK 681.5

U radu je razmatrana sinteza kontrolera sa tahometarskom povratnom spregom i unaprednom kompenzacijom momenta poremećaja, brzinske i akceleracijske greške. Teško je dobiti željene performanse sistema kada se algoritam upravljanja zasniva samo na matematičkom modelu robota. Za generisanje dodatnog momenta pogona po zglobovima, kojim se kompenzuju neodredjenosti, koristi se neuronska mreža. Kao kompenzator se upotrebljava dvoslojna neuronska mreža. Glavni zadatak sistema upravljanja je praćenje zadate trajektorije. Simulacije su uradjene u MATLAB-u za robot $R_z R_y R_y$ minimalne konfiguracije.